Development of an Optical Occupant Position Sensor System to Improve Frontal Crash Protection

Presented at the 18th International Technical Conference on the Enhanced Safety of Vehicles

May 19-22, 2003

Nagoya, Japan

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DEVELOPMENT OF AN OPTICAL OCCUPANT POSITION SENSOR SYSTEM TO IMPROVEMENT FRONTAL CRASH PROTECTION

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Paper Number 426

ABSTRACT

Considerable research has been initiated to develop countermeasures to mitigate injuries to persons, particularly children, who are present or out-of-position at the time of airbag deployment. This paper reports on the development of a camera-based optical occupant position sensor system that can be used with multi-stage inflation technologies for modulating airbag deployment.

INTRODUCTION

In motor vehicle crashes where an occupant has been seriously or fatally injured from a deploying airbag, a common finding has been that the occupant was in close proximity to the airbag (or out-of-position) at the time of deployment. The occupant may have been out-of-position for a variety of reasons including: driver loss of consciousness, pre-impact braking, multiple impacts, rearward-facing child seat installation, or late firing of the airbag after the occupant has already been forced against the airbag by the crash deceleration. Considerable research has been initiated to develop new or enhanced injury countermeasures to mitigate injuries to persons, particularly children, who are out-of-position at the time of airbag deployment. This paper reports on the development of a low-cost occupant position sensor system based on a single CMOS camera that can be used in conjunction with dual-stage or multi-stage inflation technologies for modulating airbag deployment.

The occupant position sensor system uses a CMOS camera in conjunction with pattern recognition algorithms for the discrimination of out-of-position occupants and rearward-facing child safety seats. A single imager, located strategically within the occupant compartment, is coupled with an infrared LED that emits unfocused, wide-beam pulses toward the passenger volume. These pulses, which reflect off objects in the passenger seat and are captured by the camera, contain information for classification and location determination in approximately 10 milliseconds. The decision algorithm processes the returned information using a uniquely trained neural network system. The logic of the neural network system was developed through extensive in-vehicle training with thousands of realistic occupant size and position scenarios. Although the optical occupant position sensor can be used in conjunction with other technologies, such as weight sensing, seatbelt sensing, crash severity sensing, etc., it is a standalone system meeting the requirements of FMVSS208.

In the early 1990's, ATI developed a scanning laser radar optical occupant sensor that had the capability of creating a three dimensional image of the contents of the passenger compartment. After proving feasibility, this effort was temporarily put aside due to the high cost of the system components. ATI then developed an ultrasonic-based occupant sensor that was commercialized and is now in production on some Jaguar models. ATI has long believed that optical systems would eventually become the technology of choice when the cost of optical components came down. This has now occurred and for the past several years, ATI has been developing a variety of optical occupant sensors. This paper will report on one low-cost camera-based optical system that is now ready for commercialization for high volume production.[1]

ATI's first camera-based optical occupant sensing system was an adult zone-classification system that detected the position of the adult passenger. Based on the distance from the airbag, the passenger compartment was divided into three zones, namely safe-seating zone, at-risk zone, and keep-out zone. This system was implemented in a vehicle under a cooperative development program with NHTSA. This proof-of-concept was developed to handle low-light conditions only. It used three analog CMOS cameras and three near-infrared LED clusters. It also required a desktop computer with three image

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[1] For a more complete discussion of ATI occupant sensor systems, see the following US Patents: 05653462, 05694320, 05822707, 05829782, 05835613, 05485000, 50488802, 05901978, 05943295, 06309139, 06078854, 06081757, 06088640, 06116639, 06134492, 06141432, 06168198, 06186537, 06234519, 06234520, 60242701, 06253134, 06254127, 60270116, 06279946, 60283503, 06324453, 06325414, 06330501, 06331014, RE37260, 06393133, 60397136, 06412813, 06422595, 06452870, 06442504, 06445988 as well as others published more recently.

acquisition boards. The locations of the camera/LED modules were: the A-pillar, the IP, and near the overhead console. The processing speed of the system was close to 50 fps giving it the capability of tracking an occupant during pre-crash braking situations – that is a dynamic system.

The second camera optical system was an occupant classification system that separated adult occupants from all other situations (i.e. child, child restraint and empty seat). This system was implemented using the same hardware as the first camera optical system. It was also developed to handle low-light conditions only. The results of this proof-of-concept were also very promising.

Please note that both systems above were trained to handle camera blockage situations, i.e. the systems still functioned well even when two cameras were blocked. It was decided to develop a single-camera stand-alone system that is FMVSS208-compliant, and price-competitive with weight-based systems but with superior performance. Thus, a third camera optical system (for occupant classification) was developed. Unlike the earlier systems, this system used one digital CMOS camera and two high-power near-infrared LED's. The camera/LED module was installed near the overhead console and the image data was processed using a laptop computer. This system was developed to divide the occupancy state into four classes: 1) adult; 2) child, booster seat and forward facing child seat; 3) infant carrier and rearward-facing child seat; 4) empty seat. This system consisted of two subsystems: a nighttime subsystem for handling low-light conditions, and a daytime subsystem for handling ambient-light conditions. Although the performance of this system proved to be superior to the earlier systems it exhibited some weakness mainly due to a non-ideal aiming direction of the camera.

Later, a fourth camera optical system was implemented using near production intent hardware using, for example, an ECU (Electronic Control Unit) to replace the laptop computer. In this system, the remaining problems of earlier systems were overcome. Finally, a fifth camera optical system was implemented using the same hardware but in a different vehicle. The uniqueness of this system is that it is capable of continuously tracking the occupant position. It is important to note that ATI's optical position-tracking system was implemented with a single camera, and uses technologies other than stereovision or triangulation.

This paper will not talk about all the systems above. Instead, this paper will focus on the algorithms, which represent the innovative heart of all these systems. The following algorithms will be introduced in this paper: 1) image preprocessing techniques; 2) feature extraction algorithm; 3) modular neural network architectures; 4) post neural network processing technique. Data collection, neural network training, and system performance evaluation will also be discussed in this paper.

THE PROCESS

ATI believes that an occupant sensing system should perform occupant classification as well as position tracking since both are critical information for making decision of airbag deployment in an auto accident. Figure 1 shows the ATI occupant sensing strategy. Occupant classification may be done statically since the type of occupant does not change frequently. Position tracking, however, has to be done dynamically so that the occupant can be tracked reliably during pre-crash braking situations. Position tracking should provide continuous position information so that the speed and the acceleration of the occupant can be estimated and prediction can be made even before the next actual measurement takes place.

ATI has proved that occupant classification and dynamic position tracking can be done with a standalone optical system that uses a single camera. The same image information is processed in a similar fashion for both classification and dynamic position tracking. As shown in Figure 2, the whole process involves five steps: image acquisition, image preprocessing, feature extraction, neural network processing, and post-processing.

Image Acquisition

The imaging hardware mainly consists of a digital CMOS camera, a high-power near-infrared LED, and the LED control circuit.

Three types of imaging sensors were tested and many more were investigated. The following key characteristics of the sensors were identified:
- Digital CMOS sensor (so no additional digitization hardware required)
- Spatial resolution 320×240 or 256×256 is sufficient
- Medium high dynamic range (i.e. 70-100 dB) with good image contrast

- Automotive temperature requirement (i.e. -40°C to 85°C)
- Customizable and hardware-implemented automatic exposure/gain control
- Global shutter (that simplifies the synchronization between LED's and camera)

Various near-infrared LED's were also investigated, which include the high-power LED's with special packaging for heat dissipation, and small surface-mount LED's.

Image Preprocessing

A number of image preprocessing filters have been implemented, which include noise reduction, contrast enhancement, edge detection, image down sampling and cropping, etc. Here is a list of the preprocessing filters that have been implemented so far:
- 3×3 Gaussian filter (for noise removal)
- 3×3 Laplacian filter (for edge detection)
- Kirsch filter (for detecting edges with different orientations)
- Histogram-based contrast enhancement filter
- Wavelet-based enhancement filter (including 54 wavelet functions from 7 families)
- Morphological filter (including dilation, erosion, close, open, tophat, h-dome)
- Binarization filter
- Image down-size filter (for down-sampling and cropping)

- Generic in-frame filter (i.e. a customizable window-based spatial filter)
- Generic cross-frame filter (i.e. a customizable window-based temporal filter)
- Pixel transfer filter (suitable for eliminating regions with irregular shapes)

Under daylight conditions, the image contains unwanted contents because the background is illuminated by the sunlight. For example, the movement of the driver, other passengers in the backseat, and the scenes outside the passenger window can interfere if they are visible in the image. Usually these unwanted contents cannot be completely eliminated by adjusting the camera position, but they can be removed by image preprocessing.

Feature Extraction

The image size in the current classification system is 320×240, i.e. 76,800 pixels, which is too much for the neural network to handle. In order to reduce the amount of the data while retaining most of the important information, a good feature extraction algorithm is needed. ATI's block-based multi-scale feature extraction algorithm is able to compresses the data to only a few hundred floating-point numbers while retaining most of the important information. Figure 3 shows an example of the image and its corresponding feature vector.
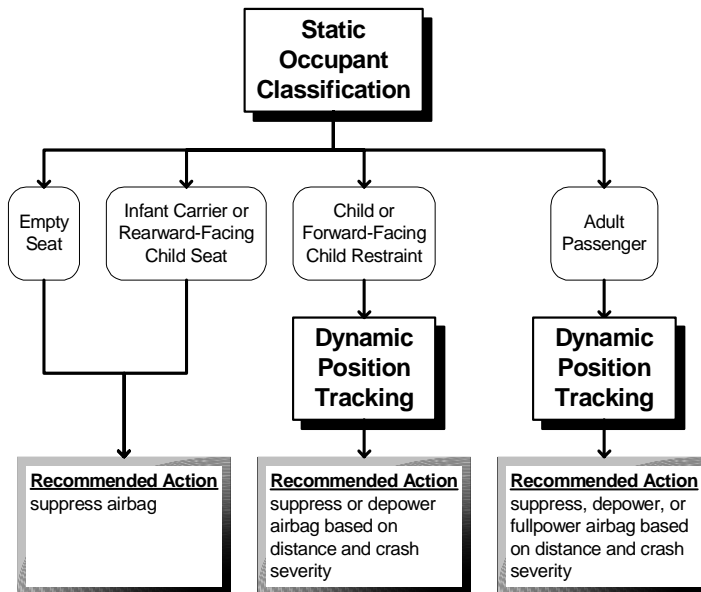

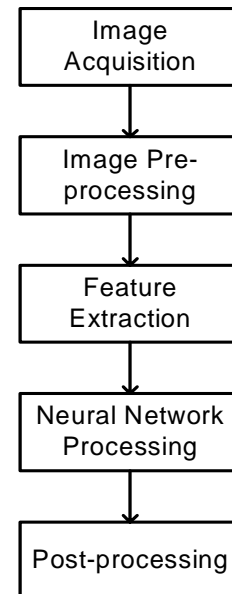**Figure 1. ATI occupant sensing strategy.**
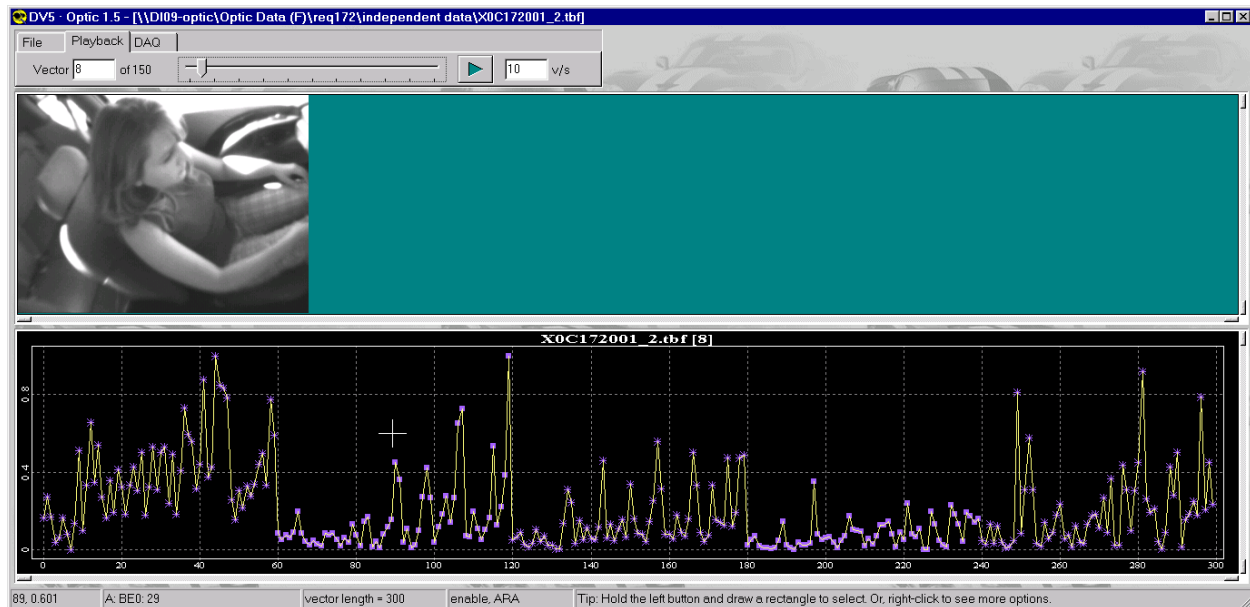

Figure 2. Processing block diagram.

Figure 3. Example of image feature extraction.

Table 1. Factors that may affect the image data.

Vehicle Configuration	Occupant	Child Restraint	Lighting Condition
▪ Seat track position ▪ Seatback recline position ▪ Other interior fixture configurations (such console, glove box, seatbelt, etc.)	▪ Height ▪ Weight ▪ Clothing ▪ Hair and facial hair ▪ Skin tone ▪ Seating position ▪ Personal objects	▪ NHTSA FMVSS208 approved 11 rear-facing child restraints, 7 forward-facing child restraints, and 4 booster seats.	▪ Nighttime condition ▪ Sunlight at different time of the day and/or different vehicle orientation ▪ Dome light ▪ Door light ▪ Headlight from other vehicle

Neural Network Processing

Once an image is converted into a feature vector, the classification decision can be made using any pattern recognition technique. Literature studies show that the neural network technique that simulates the human brain is particularly effective in pattern recognition applications. In our application, however, the patterns of the feature vectors are extremely complex. Table 1 shows a list of things that may affect the image data and therefore the feature vector. Considering all the combinations, there could be an infinite number of patterns. For a complex system like this, it is impossible to train a single neural network to handle all the possible scenarios. Studies show that, by dividing a large task into many small subtasks, a modular approach is extremely effective with complex systems.

Figure 4 shows some of the modular neural network architectures that have been tested. Particularly, the architecture in Figure 4(3) has two unique characteristics:

1) Since the outputs of all the six neural networks can be considered as binary, there are 64 possible output combinations, but only 32 of them are valid. For an untrained data pattern, it is more likely to have an invalid output combination than a misclassification. Therefore this architecture provides a way to identify "unseen" patterns.

2) Since a positive classification requires consistent outputs from three neural networks, the chance of misclassification is very small. Misclassification rate is reduced by replacing the weak classifications with "undetermined" states.

Post-Processing

The simplest way to utilize the temporal information is to use the fact that the data pattern always changes

continuously. And because the input to the neural networks is continuous, the output from the neural networks should also be continuous. Based on this idea, post-processing filters can be used to eliminate the random fluctuations in the neural network output. Here is a list of the post-processing filters that have been implemented so far:

- Generic digital filter
- Kalman filter
- Median filter
- Post-decision filter based on "age" and "locality"

Besides filtering, additional knowledge can be used to remove some of the undesired changes in the neural network output. For example, it is impossible to change from an adult passenger to a child restraint without going through an empty-seat state, and vice versa. Based on this idea, a decision-locking mechanism for eliminating undesired decision changes was implemented. Once the system stabilizes, any direct change between two non-empty-seat classes is virtually prohibited.
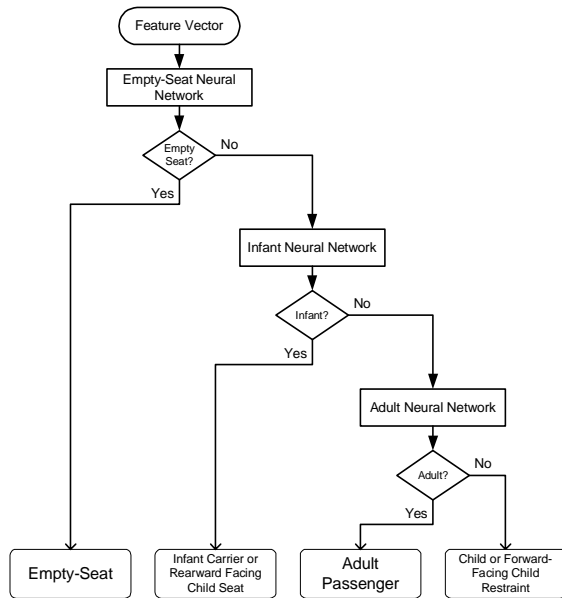
(1) Architecture #1.
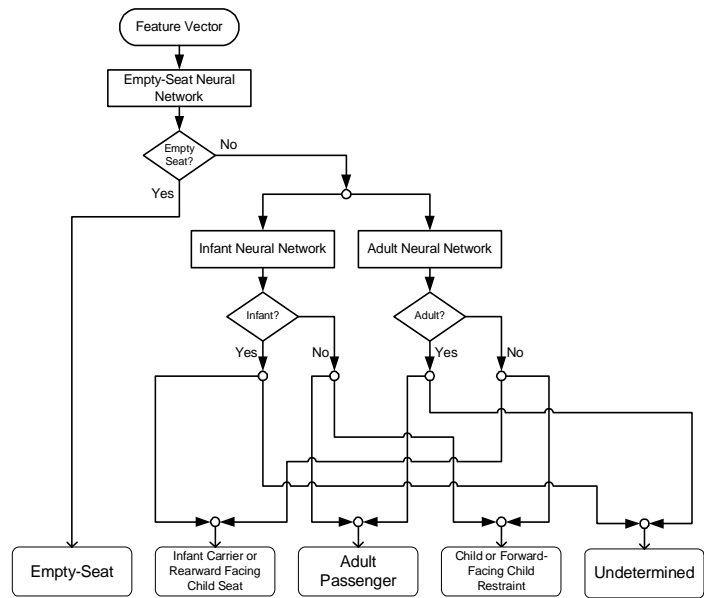
(2) Architecture #2.
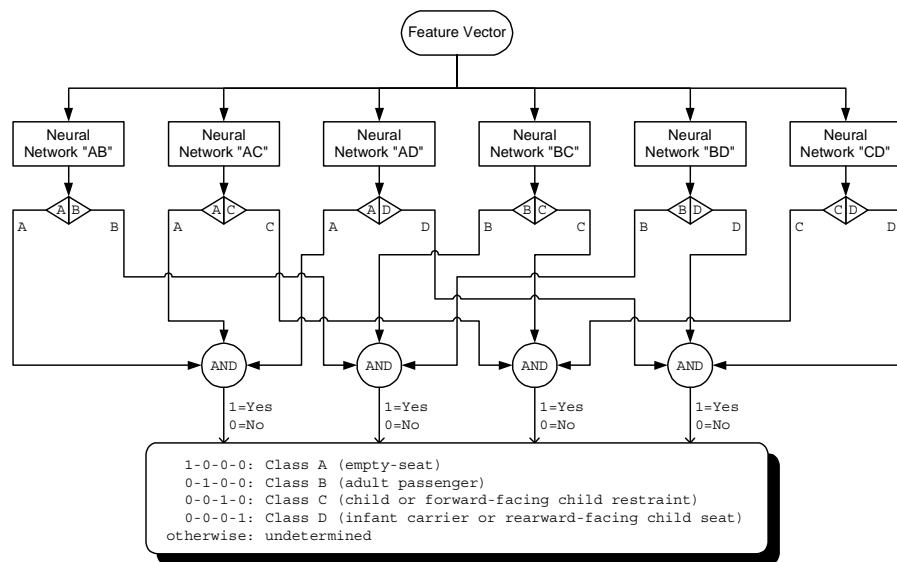
(3) Architecture #3.

Figure 4. Various modular neural network architectures were investigated.

SYSTEM TRAINING

Currently ATI implements occupant classification as two systems for handling ambient light (or daytime) conditions and low-light (or nighttime) conditions respectively. Under low-light conditions, the center of the view is illuminated by near infrared LED's. The background (including the floor, the backseats, and the scene outside the window) is virtually invisible, which makes classification somewhat easier. Classification is more difficult under ambient light condition because the background is illuminated by the sunlight, and sometimes the bright sunlight projects sharp shadows onto the seat, which creates false patterns in the feature vectors.

ATI's optical position-tracking system was also implemented with a single camera. The difficulty with the position-tracking system is to obtain the continuous distance information for training. An ultrasonic distance-tracking device was developed for this purpose. This device contains a sender (installed near the airbag) and a receiver (attached to the moving occupant), and is able to send continuous distance measurements to a PC via serial port.

A Classification System for Nighttime Conditions

The data collection on the nighttime classification system was done inside a building where the illumination from outside the vehicle was filtered out using a near-infrared filter. The data set consists of about 725,000 images, and the data distribution is shown in Table 2. The 3-network architecture shown in Figure 4(2) was used, and the performance of the whole modular system is shown in Table 3.

A Classification System for Daylight Conditions

The data collection on the daylight classification system is more complex because different sunlight conditions have to be considered. A systematic data collection matrix was made to cover both sunny conditions and overcast conditions. For sunny conditions, a timely schedule was created to cover all sunlight conditions corresponding to different time of the day. The data set consists of about 860,000 images, and the data distribution is shown in Table 4. Both the 3-network architecture in Figure 4(2) and the 6-network architecture in Figure 4(3) were used. The performance of the 3-network architecture is shown in Table 5, while the performance of the 6-network architecture is in Table 6. The results show that the 6-network architecture gives higher success rates.

A Position-Tracking System for Nighttime Conditions

The occupants were wearing an ultrasonic distance-tracking device during the data collection on the position-tracking system. After learning from the images associated with accurate distances, the system is able to track the occupant continuously as the occupant moves inside the passenger compartment. Figure 5 demonstrates the tracking capability, where the red lines indicate the readings from the ultrasonic distance-tracking device and the blue lines are outputs from the neural networks. The spikes in the red lines were due to the fact that the ultrasonic distance-tracking device has limited field of view and it loses signal when the occupant turns their head away from the receiver.

Table 2. Distribution of the database of nighttime conditions.

Adult	Child and FFCR (Forward-Facing Child Restraint)	Infant Carrier and RFCS (Rearward-Facing Child Seat)	Empty Seat
38.71%	25.14%	27.27%	8.88%

Table 3. Performance of the classification system for nighttime conditions.

|		Classified As				
		Adult	Child & FFCR	Infant Carrier & RFCS	Empty Seat	Undetermined
Target Class	Adult	**97.30%**	1.83%	0.22%	0.01%	0.64%
	Child & FFCR	0.92%	**98.44%**	0.62%	0.02%	0%
	Infant Carrier & RFCS	0.09%	0.62%	**98.60%**	0%	0.69%
	Empty Seat	0%	0%	0%	**100%**	0%

Table 4. Distribution of the database of daylight conditions.

Adult	Child and FFCR (Forward-Facing Child Restraint)	Infant Carrier and RFCS (Rearward-Facing Child Seat)	Empty Seat
47.72%	11.98%	32.09%	8.21%

**Table 5. Performance of the classification system for daylight conditions (3-network architecture).**

		Classified As				
		Adult	Child & FFCR	Infant Carrier & RFCS	Empty Seat	Undetermined
Target Class	Adult	**97.34%**	1.06%	0.32%	0.35%	0.93%
	Child & FFCR	0.88%	**98.72%**	0.37%	0.03%	0%
	Infant Carrier & RFCS	0.33%	1.05%	**97.69%**	0.04%	0.89%
	Empty Seat	0.02%	0.10%	0.01%	**99.87%**	0%

Table 6. Performance of the classification system for daylight conditions (6-network architecture).

		Classified As				
		Adult	Child & FFCR	Infant Carrier & RFCS	Empty Seat	Undetermined
Target Class	Adult	**98.45%**	0.48%	0.82%	0.06%	0.19%
	Child & FFCR	0.15%	**99.63%**	0.15%	0.01%	0.06%
	Infant Carrier & RFCS	0.70%	0.19%	**98.97%**	0%	0.14%
	Empty Seat	0.03%	0%	0%	**99.94%**	0.03%
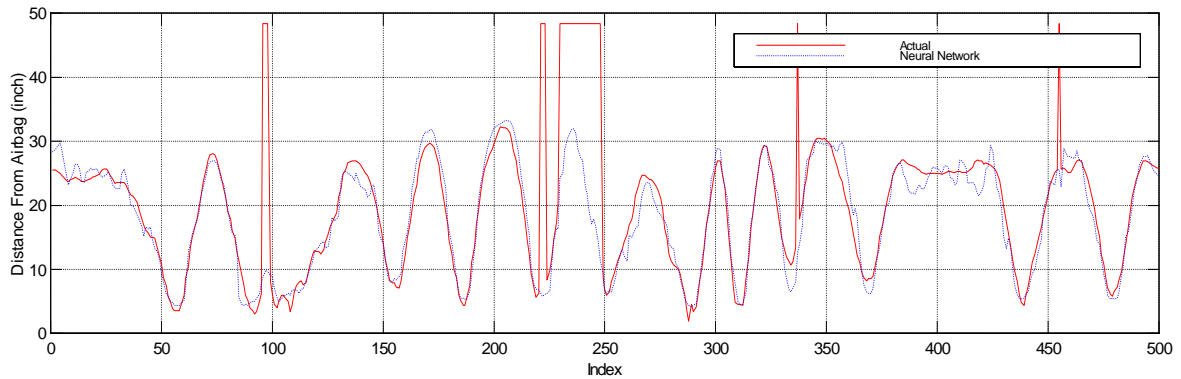
(1) 50%-tile female in light color clothes.
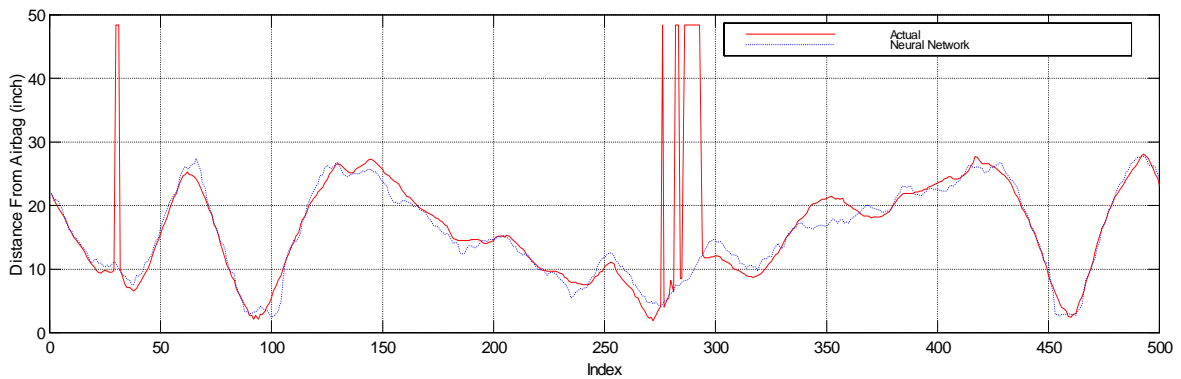
(2) 95%-tile male in dark color clothes.

Figure 5. The position-tracking system tracks the distance between the moving occupant and the airbag.
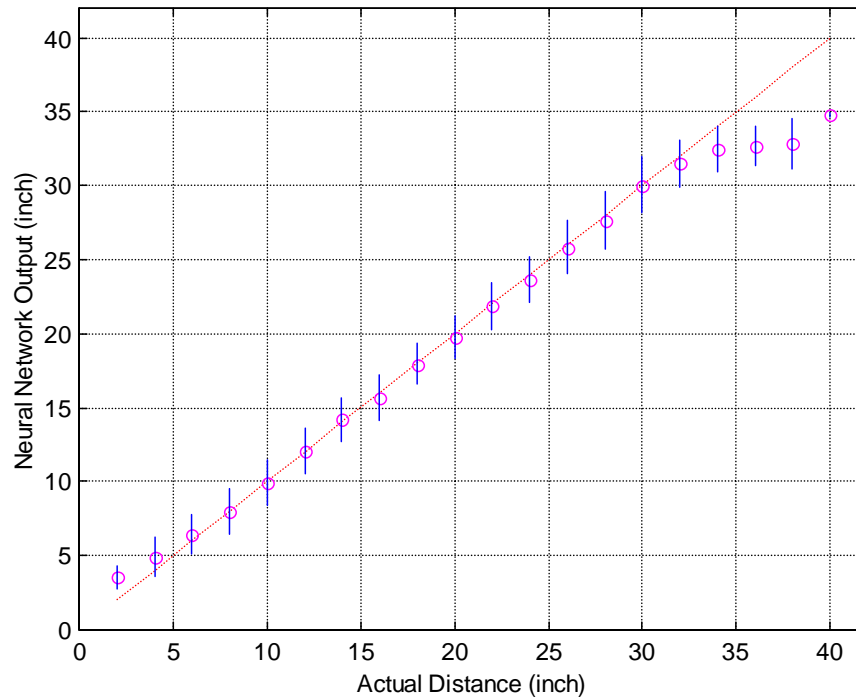
Figure 6. The accuracy of the position-tracking system.

The accuracy of the position-tracking system is shown in Figure 6. One can see that the accuracy starts to decrease when the distance is below 5 inches or above 32 inches, which was due to the limitation of the ultrasonic distance-tracking device. Please note that this system was trained with a rather small database that contains only 36,000 images.

CONCLUSIONS AND DISCUSSIONS

In this paper, the technology of a standalone optical occupant sensing system using a single camera was introduced. During the development of the system, new image preprocessing techniques were implemented, the feature extraction algorithm was developed, new neural network architectures and new post-processing techniques were explored, data collection techniques were improved, new modular neural networks were trained and evaluated, many software tools were created or improved, and also problems present in data collection and hardware installation were identified.

It is important to note that the classification/position-tracking accuracies reported here are based on single images and when the post-processing steps are included the overall system accuracy approaches 100%. This is a substantial improvement over previous systems even though it is based on a single camera. Some additional improvement can be obtained through the addition of a second camera. Nevertheless, the system as described herein is cost-competitive with a weight-only system and substantially more accurate. This system is now ready for commercialization where the prototype system described herein is made ready for high volume serial production.